A New Cognitive-Based Massive Alarm Management System in Electrical Power Administration

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Abstract: **This paper presents a methodology that integrates several available techniques to manage the massive amount of alarm signals in electrical power dispatch control centres, as well as the contribution of each entity involved in the system. Artificial intelligence techniques that can be used in this problem are reviewed here based on the available information. The final objective is to find the root cause of avalanches of alarms (failure tree) and to reduce their number through grouping or clustering techniques so that the EEMUA 191 standards are followed. Even though other contributions in this topic have been made before, the alarm management problem continues to be practically unsolved for many applications in industry. Here, the integration is developed using the ontology of each system domains, i.e., the ontology corresponding to the alarms, controls, events, energy flow and trigger sequence. Additionally, in this methodology, a rule based expert system is used to treat the alarms with a neural net based approach to treat the historical database of alarms and failures.**

Keywords: Cognitive Systems, Alarm Management Systems, Artificial Intelligence, Electrical Power.

I. INTRODUCTION

Based on the EEMUA 191 Standard, an operator has the capacity to effectively handle an average of 1 alarm each 10 minutes. However, there are, control rooms that register about two thousand alarms per day. In critical cases, like in electrical power dispatch control centres, that amount could reach more than forty thousand alarms per day. This amount is much greater than the average that one operator can manage effectively and efficiently. Although, there are several commercial products design to attend the alarm administration problem, the technical literature does not present a methodology that integrates all the entities and their domains that are involved in the alarm administration process. The use of ontologies allows the creation of a standard representation (conceptualization) of the domains so that they can be reused in other electrical networks. At the same time, the information system becomes interchangeable with the ontologies. Due to the high complexity of electrical networks, including their control and administration, and their high level of sophistication, the use of artificial intelligence techniques is recommended.

The use of a knowledge-based system as a tool to solve this type of problem has been recommended by the literature. Several authors point out that the knowledge representation can be useful in several applications. Similarly, the long-term objective is obviously to develop a standard representation that can be shared and reused in electrical utilities applications. (Bernaras, A., et al., 1996). The use of an expert system and a deductive learning method in the control process can be considered innovative and endowed of an adequate risk evaluation capability (HSE, 2007).

Other authors, (Lee, CH., et al., 2004) affirm that the fault tree analysis is a solution to the problem. These authors assert that the next step in Data Mining will be to implement software for fault detection, prediction and analysis. Some of these software packages will use decision trees as an engine within the diagnostic system. This engine must be able to get knowledge from fault patterns in ways that they can be recognized when they occur. On the other hand, Julisch, K., (apud Broderick, 1998), Manganaris, et al., 2000, Axelsson, 2000, Bloedorn, et al., 2000 y Julisch, 2001), assert that the used of clustering methods to get an appropriate response is still a challenge. This point of view confirms that there is yet too much to do on this matter.

Finally, it is important to bring into focus, that in the long term, the subsequently task should consist of getting to a predictive alarm administration level as established by the EEMUA 191 Standard in one of its goals. In order to achieve this goal it is necessary to have a full adaptive system, in ways that it can itself predict the future state of the plant and the set point configuration based on the knowledge of the requirements at a particular moment.

This is still a desired result and for this reason it is being researched currently and it will be a significant step towards achieving the forward paradigm changes and the new handle models (Brown, C. 2003).

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Judging by (Bernaras, A., 1996), there are several appropriate characteristics that define the fault diagnosis systems as follows:

- It does require a standard representation of the electrical network.
- In the past, each new system used a different representation. In spite of that, the knowledge about the electrical network is very similar in all cases.

Present and future work in this area has the condition that the representation of the knowledge must be reusable in different applications and could be shared by many electrical utilities.

There are many works that have attempted to solve the alarm administration problem; however, they have failed because of the necessity of integrating the methodologies with entities and their domains (Andow P., 2005; Huebner F., 2001; Bransby ML., et al.,1998).

II. THE ONTOLOGICAL CONCEPT

Based on Noy, N, et al., (2005), the literature on artificial intelligence gathers several definitions; many of which contradict each other. This author defines an Ontology as an explicit formal description of concepts in a domain (classes or sometimes called concepts), describing several characteristics and attributes of the concept or class (slots or role constraint). The slots describe properties from classes or instances.

In this point it is necessary to clarify the difference between the ontology development and the classes design and their relationships with the Object-Oriented Programming. Based on Noy, N., et al., (2005), the Object-Oriented Programming has focused mainly around classes-method, i.e., one programmer takes its design decisions based on the operational properties of one class, whereas an ontology designer does it taking the structural properties from one class. In this way, an Object-Oriented electrical network might be divided as follows:

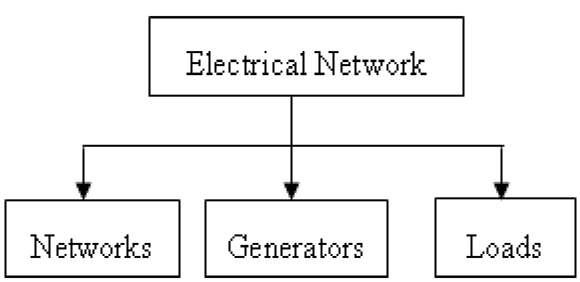

Fig. 1 Object-Oriented Classes Hierarchy.

The classes' hierarchy based on the operational function system is presented in fig. 1. That is, the entire electrical network is composed of three high classes. These are: The generation class, the network class (bars, branch circuits, electrical lines, transformers, etc.) and the loads class (Manzoni, A., et al., 1999).

On the other hand, for an ontology programming developer, the power electrical network will have the following hierarchical structure:

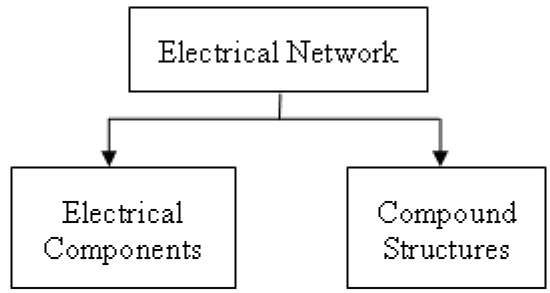

Fig. 2 Classes Hierarchical from a power electrical systems ontology-oriented design

It can see that the classes' hierarchy is now represented for the structural components. That is, the high classes are represented for the electrical components or discrete elements (non disagreeable entities like, lines, transformers, busses, etc.) and by compound components (disagreeable entities like, substations, connections, voltage levels, etc.) (Bernaras, A., et al., 1996). The framework here is represented by divisions according with the network schema.

Thus the ontologies for the real world applications are very complex and they need to be modularized. In the power system case, the fault diagnosis general ontology is a small combination of ontologies. To analyze the behaviour of an electrical network in detail, Bernaras, A., et al., (1996) have identified five relevant and different ontologies allied with each other like shown in figure 3. These are:

Flow Ontology (Transport Ontology) (FO): This is defined for the connectivity. That is, the involved elements in the electrical energy flow, and not in the generation or the demand of power.

Control Logic Ontology (CO): It contains the network elements that are related to the failure detection and the automatic reconfiguration (for example: relays cut off elements, breakers, etc.)

Events Ontology (EO): It describes the kind of events that occur in the network and which are diagnosed by the application.

Alarm Ontology (AO): It describes the alarms that are generated to provide information about the operations of the dynamic appliances

Trip Sequence Ontology (TO): It describes the kind of trips or cut-off appliances.

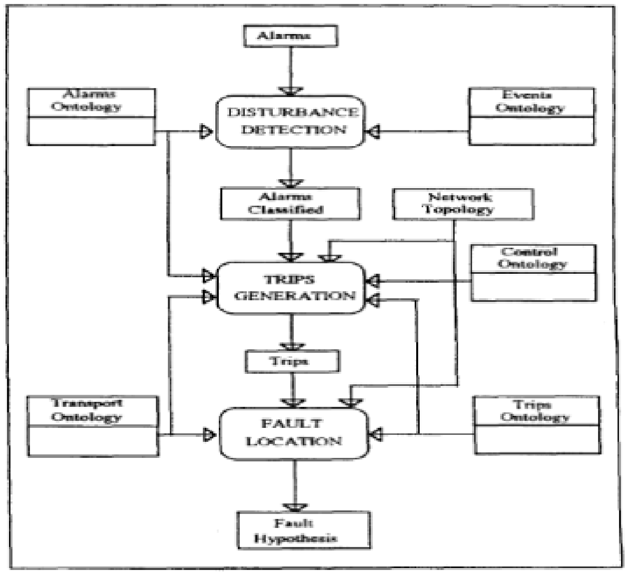

Fig.3 Use of the Ontologies for Fault Hypothesis

These ontologies are not completely independent, and thus, relate to each other. For the purpose of reusability, they have been designed to maximize cohesion within an ontology and minimize coupling between them. The relations between ontologies have been expressed as views that one ontology has about the concepts described in another. The use of the ontologies within the task of the application is showed in fig. 3 (from Bernaras, A., et al., 1996). The task "Disturbance Detection" identifies the existence of a disturbance and determines the type of disturbance. The "Trips Generation" task generates a synthesized view of the reaction of the protective relays and breakers to the occurrence of the fault. The "Fault Location" task selects from all possible fault hypothesis the most likely one. The main input to the "Disturbance Detection" task are the alarms received from the network (Normally by the SCADA system). This information in addition with the knowledge contained in the alarms ontology and the events ontology, produce the classification of the alarms according to the type of disturbance produced.

In the "Trips Generation" task, the information provided by the classified alarms is processed together with the topology of the network and the knowledge contained in the alarm ontology, the control ontology, the trips ontology and the flow ontology. The output are the trips that the operator in the control room sees as a synthesized information of the reaction of the network. The information provided by these trips is processed in the "Fault Location" task, together with the topology of the network and the knowledge contained in the trips and flow ontologies. The final task is to get a fault hypothesis.

III. PROPOSED METHODOLOGY AND AVAILABLE RESOURCES.

The following figure (fig.4) shows the proposed model. The information to develop the model was taken from a real life information produced in the control center at an hydroelectric power plant located in the Republic of Panama.

From an inductive reasoning perspective, it is possible to see, the integration of elements or entities that take place in the alarm administration system.

The final objective of this research effort is to get an alarm tree for the alarm avalanche that might occur in any dispatch centre, starting from the information resources (alarms, historic fault or alarm data base, network physical connectivity, control logic, etc.) and artificial intelligence techniques (expert systems, neural networks or neuro-fuzzy networks). Figure 4, shows the inductive reasoning through which the alarm trees is to be developed, so the user can identify the root cause of the alarm avalanche.

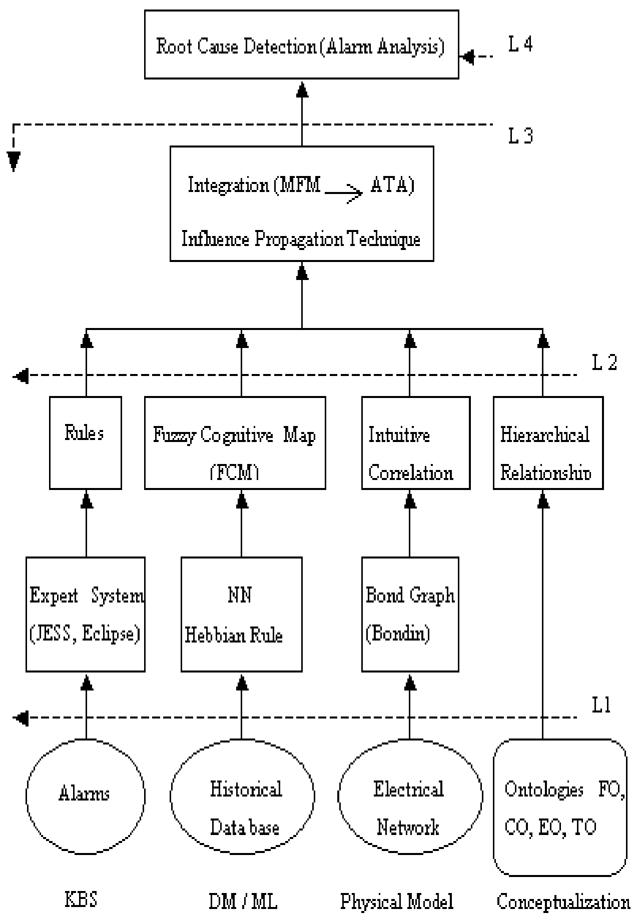

Fig. 4 Proposed Methodology

Under the L1 (level 1), only information is found. There is an alarm list that can be provided by the SCADA system. In addition, there is a historical events database which contains a great amount of information to be processed solely by the system's operators. Moreover, at this level there is the information about the electrical network (connections, lines, transformers, bars, etc.). Finally there is a logical control framework and control policies.

At the second level (L2), there is an expert system that provides rules on the basis of the alarms. In this case, JESS was used as the inference engine and Eclipse as JAVA editor. After interviewing seven experts in six sessions of approximately 35 hours in total, the Expert System generated 256 rules, from 156 digital alarms and 15 analog alarms. The rule-based expert systems uses **IF-THEN** rules. An example from the rules is shown in the following schema:

Rule #	Rule	Associated Failure	Recommended Action
148 a	**IF** Failure in breaker 23M22 occurs **AND** Breaker 23M22 is off. **THEN** Breaker 23M22 is not closed **OR** is incorrectly closed	Breaker 23M22 Failure	Check the associated relay information with the breaker 23M22

With respect to the historical database treatment, a co relational statistics analysis tool was used, in order to obtain values to be as input for the neural network.

A typical "Fuzzy Cognitive Map Neural Network" (FCM) based on Nonlinear Hebbian Rule was implemented. The term "Fuzzy Cognitive Map" was presented by Kosko to embody a cognitive map model (Kosko, B., 1997). Hebb's theory of learning is based on the observation that in biological systems when a neuron contributes to the firing of another neuron, the connection or pathway between the two neurons is strengthened (Luger, G., 2005). Based on this proposition or principle, the effect of strengthening between two neurons can be simulated mathematically by adjusting the weight of their connections.

On the other hand, FCM is a soft computing technique for modelling systems. It combines synergistically the theories of neural networks and fuzzy logic. The developing of FCM relies on human experience and knowledge, and thus, FCM exhibit weaknesses and dependence on the human expert and can be appropriated to explicit the knowledge, which has been accumulated for years observing the operation an behaviour of a complex system (Papageorgiou, E., et al., 2003). This technique describes two significant features:

- Causal relationships between nodes are fuzzified.
- The systems has dynamical involving feedback.

As an ANN (artificial neural network), in a FCM framework, the concepts are represented by neurons and the causal relationships by weighted links. The weight interconnections (W_{ii}) represent the direction and degree with which concepts influence the value of the interconnected concepts. The algorithm is as follow:

Be Ni and N_j two nodes that are interconnected with a strength like the one illustrated on figure 5.

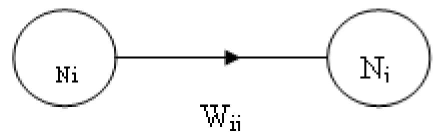

Fig. 5 Interconnection strength between two nodes.

Where W_{ij}= [-1, 1].

If $W_{ij}>0$, then, there is a positive causality between concepts N_i and N_j; i.e., the increase in the value of N_i leads to the increase on the value of N_j, and vice versa.

If $W_{ij}<0$, then, there is a negative causality between concepts N_i and N_j; i.e., the increase in the value of N_i, leads to the decrease on the value of N_j, and vice versa.

If $W_{ij}=0$, then, there is no relationship between N_i and N_j.

The value of each concept can be calculated by applying the following rule:

$$A_j^{(k+1)} = f(A_j^{(k)} + \sum_{\substack{i=1 \\ i \neq j}}^{n} A_i^{(k)} * W_{ij})$$

and the training weight algorithm takes the following form:

$$W_{ij}^{(k)} = W_{ij}^{(k-1)} + \eta_k^{Ai}\left(A_j^{(k)} - A_i W_{ij}^{(k-1)}\right)$$

Where, $A_j^{(k+1)}$ is the value of concept N_j at time k+1 and $A_j^{(k)}$ is the value of concept N_i at time k, W_{ij} is the weight of the interconnection between concept N_i and concept N_j, and f is the sigmoid threshold function and η is the learning rate.

The expert's opinion is represented through the definition of the Fuzzy Set which describes the relationship between two concepts and so determinates the grade of causality between them. This dependence can be improved through learning techniques based on Non Linear Hebbian Learning Rule (NHL) by modifying the FCM weight matrix.

Papageorgiou, E., et al., (2003), proposed an approach based on NHL, which can change the FCM model by triggering at each iteration step and changing their values. The schematic representation of NHL training algorithm from this authors is showed in figure 6.

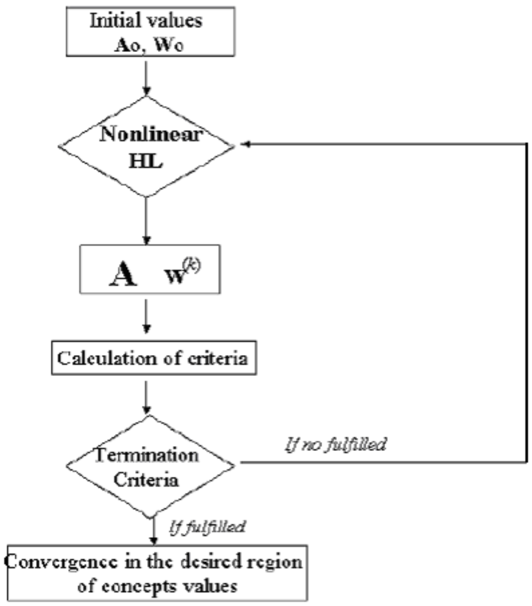

Fig. 6 NHL Training Algorithm

One year of historical database was used in order to get W^0 matrix (weight initial matrix) and the vector A^0 (initial vector of the concept values) was determined by the experts.

The Network topology was developed as a Bond Graph representation. BONDIN is a software developed by Dr. Gregorio Romero at the Polytechnic University of Madrid. It is a good tool to get the representation of the network. It can obtain the mathematic model and a Bond structure among equipments and appliances.

At the third level (L3) of the methodology is the integration algorithm. The known technique as Multilevel Flow Modelling (MFM) is used. The multilevel flow modelling is a functional modelling technique. It models diagrammatically a system from the new point of the means-end dimension. This technique was invented by Professor Morten Lind in 1990. Gofuku, et al., 2006, developed an influence propagation technique based on MFM model to derive plausible counter actions in anomalous situation of a plant. The technique is applied to generate automatically FTA from MFM.

Until here, at level 4 (L4) all these results are integrated in a programming package that has an interface with Protégé. Protégé is a software that can build ontologies in a tree form. In this way, we obtain the alarm tree and its root cause.

IV. CONCLUSIONS

The proposed method points out to the integration of four domains. That is, the artificial intelligence techniques, the historical events data-base, the topology of the network and the ontologies.

At this point, this research effort has produced partial results such as The Expert System, The Network Topology, the FCM and the Ontologies Topology. Main difficulties have been found in the generation of the Expert Systems and the FCM model since it was difficult to convert information from the experts in a set of understandable and logical rules. In addition, defining a concept value in the FCM has presented difficulties due to the fact that the experts had doubts about this value and its meaning. The integration method using FTA from MFM is not already finished, but the expected results are optimist.

V. FURTHER WORKS.

The Technological University of Panama and the Polytechnic University of Madrid, in the last years have been worked together on a common research line in Intelligent Control.

As further work, it has been proposed the development of the different levels proposed in the methodology with about 20 or 30 years of information stored in the historical database described in the model.

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